

Poisson limits for empirical point processes

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Abstract

Define the scaled empirical point process on an independent and identically distributed sequence $\{Y_i : i \leq n\}$ as the random point measure with masses at $a_n^{-1}Y_i$. For suitable a_n we obtain the weak limit of these point processes through a novel use of a dimension-free method based on the convergence of compensators of multiparameter martingales. The method extends previous results in several directions. We obtain limits at points where the density of Y_i may be zero, but has regular variation. The joint limit of the empirical process evaluated at distinct points is given by independent Poisson processes. These results also hold for multivariate Y_i with little additional effort. Applications are provided both to nearest-neighbour density estimation in high dimensions, and to the asymptotic behaviour of multivariate extremes such as those arising from bivariate normal copulas.

Keywords: multiparameter martingales; point processes; density estimation; multivariate extremes; local empirical processes

Running title: Empirical point processes

1 Introduction

Point processes and their limits arise naturally in many areas of statistics, and have a number of applications ranging from survival analysis to spatial statistics. Point processes also arise in probability theory as limits for extreme value processes, in studying limits of sums of stable non-Gaussian variables and in queuing models. Of course the Poisson process is a fundamental concept in martingale theory. Weak convergence of the empirical point process underlies many applications, and this paper employs the relatively recent area of multiparameter martingales to establish a novel and unified approach to proving such limits for scaled empirical point processes. Although various elegant and powerful methods have been developed for particular classes of problems, the generalized martingale approach provides an extremely simple, dimension-free method of addressing a variety of old and new distributional questions.

Given a random sample of random vectors $\{Y_i : i \leq n\}$ in \mathbb{R}^d and a suitable class of sets $\{A\}$, the empirical point process is defined by

$$N_A^{(n)} = \sum_{i=1}^n \mathbb{I}_{\{Y_i \in A\}}.$$

As noted above, the weak convergence of $N_A^{(n)}$ has been extensively studied using a variety of methods. In particular, a strong approximation approach can be used to establish weak convergence of the local empirical process (see Einmahl, 1997, and the references therein):

$$L_{n,x}(t) = \frac{1}{n} \sum_{i=1}^n \mathbb{I}_{\{Y_i \in [x-ta_n, x+ta_n]\}}, \quad t \in [0, 1],$$

where now the Y_i 's are univariate. If the sequence of constants, a_n , is appropriately chosen then the limit process is homogeneous Poisson. However, this strong Poisson approximation is difficult to implement (or at least cannot be extended directly) if one wants to study the joint behaviour of

$$(L_{n,x_1}(\cdot), \dots, L_{n,x_m}(\cdot)),$$

i.e. when estimating the density of Y_1 simultaneously at (x_1, \dots, x_m) (see Section 4.1). Even in the Gaussian case, where simultaneous approximation by independent Wiener processes is known, Deheuvels *et al.* (2000) points out that a major technical difficulty arises in proving independence at separate x_i .

The aim of this paper is to develop a general and natural approach to *weak* Poisson limits for empirical point processes. It is based on the multiparameter martingale theory of Ivanoff and Merzbach (2000) and requires only the simple computation of so-called *-compensators to identify Poisson limits for scaled empirical point processes. The compensator method exploited here is particularly attractive in that it is independent of the dimension of the underlying random vectors, and so easily generalizes results from the univariate to the multivariate case. In addition, the martingale approach allows one to handle the

joint behaviour at multiple points with ease through a judicious definition of the associated history (filtration). In particular, we shall show that the asymptotic behaviour of the local empirical process at distinct points x_1, \dots, x_m can be described by independent Poisson processes, an intuitive but otherwise technically challenging result.

The method has additional benefits. First, only (multivariate) regular variation of the density f of Y_1 is required, and the limits are explicitly written in terms of f . Indeed, we can discover the appropriate scaling constants even when f is regularly varying but $f(0) = 0$, i.e. a case with inhomogeneous Poisson limits excluded in Borisov (2000). characterize the distributional behaviour of joint extremes for different bivariate copulas. This recovers Einmahl (1997, Corollaries 2.4 and 2.5) where the limit Poisson process has a product mean measure, but also extends to more complex cases (Corollary 4.5). In particular, we can identify extreme value limits for copulas with asymptotically dependent multivariate extremes more simply than methods employing multivariate regular variation (c.f. Resnick, 1987).

The paper is structured as follows. The next section will review key elements of the theory of multi-parameter martingales and in particular, the use of *-compensators in proving weak convergence of a sequence of point processes. Section 3 defines the scaled empirical point process generated by a sample and establishes point process limits for such processes. This proceeds in steps from the classical non-negative and univariate case (yielding limits similar to those for extreme value processes), to the multivariate and multidimensional cases. In each case the proof simplifies to the straightforward calculation of *-compensators, and highlights the universality of the martingale approach. Section 4 on applications illustrates the utility of our results by establishing for the first time weak limits for nearest-neighbour estimates of joint densities (again at several points simultaneously), and by providing new extreme value limits for multivariate copulas.

2 Notation and background: Point processes and martingale methods

We provide a brief introduction to point processes and martingale methods indexed by general Euclidean spaces using the set-indexed framework introduced in Ivanoff and Merzbach (2000). We need definitions mimicking those for martingales indexed by \mathbb{R}_+ .

Set $T = \mathbb{R}^d$ or \mathbb{R}_+^d , and $\mathcal{A} = \{A_t = [0, t] : t \in T\} \cup \{\emptyset\}$, where we interpret $[0, t]$ in the obvious way if $t \notin \mathbb{R}_+^d$. Set-inclusion on \mathcal{A} induces a partial order, \preceq , on T : $s \preceq t$ if and only if $A_s \subseteq A_t$. This is not the usual partial order on \mathbb{R}^d : e.g. $\{0\}$ is the (unique) minimal element, and all quadrants are equipped with their own partial order. In particular, if $T = \mathbb{R}$, points with different signs are incomparable. This special structure permits us to define a 2^d -sided martingale theory.

The semi-algebra \mathcal{C} is the class of all subsets of T of the form

$$C = A \setminus B, \quad A \in \mathcal{A}, \quad B \in \mathcal{A}(u),$$

where $\mathcal{A}(u)$ denotes the class of sets which are finite unions of sets from \mathcal{A} . Let (Ω, \mathcal{F}, P) be any complete probability space. A filtration indexed by $\mathcal{A}(u)$ is a class $\{\mathcal{F}_A : A \in \mathcal{A}(u)\}$ of complete sub- σ -fields of \mathcal{F} where $\forall A, B \in \mathcal{A}(u)$, $\mathcal{F}_A \subseteq \mathcal{F}_B$ if $A \subseteq B$, and (Monotone outer-continuity) $\mathcal{F}_{\cap_i A_i} = \cap \mathcal{F}_{A_i}$ for any decreasing sequence (A_i) in $\mathcal{A}(u)$ such that $\cap_i A_i \in \mathcal{A}(u)$. For consistency, we define $\mathcal{F}_T = \mathcal{F}$. We may associate σ -algebras with sets in \mathcal{C} : for $C \in \mathcal{C} \setminus \mathcal{A}$, let $\mathcal{G}_C^* = \vee_{B \in \mathcal{A}(u), B \cap C = \emptyset} \mathcal{F}_B$, and for $A \in \mathcal{A}, A \neq \emptyset$, define $\mathcal{G}_A^* = \mathcal{F}_\emptyset$. A (\mathcal{A} -indexed) *stochastic process* $X = \{X_A : A \in \mathcal{A}\}$ is a collection of random variables indexed by \mathcal{A} , and is *adapted* if X_A is \mathcal{F}_A -measurable for every $A \in \mathcal{A}$. By convention, $X_{\{0\}} = 0$.

A process $X : \mathcal{A} \rightarrow \mathbb{R}$ is *increasing* if for every $\omega \in \Omega$, the function $X(\omega)$ can be extended to a finitely additive function on \mathcal{C} satisfying $X_{\{0\}}(\omega) = 0$ and $X_C(\omega) \geq 0$, $\forall C \in \mathcal{C}$, and such that if (A_n) is a decreasing sequence of sets in $\mathcal{A}(u)$ such that $\cap_n A_n \in \mathcal{A}(u)$, then $\lim_n X_{A_n}(\omega) = X_{\cap_n A_n}(\omega)$. A process $N = \{N_A, A \in \mathcal{A}\}$ is a *point process* if it is an increasing process taking its values in \mathbb{N} , and almost surely for any $t \in T$, $N_{\{t\}} = 0$ or 1. Note that if N is a point process on $T = \mathbb{R}$, then $N_t := N_{[0, t]}$ (for t positive or negative) and not $N_{(-\infty, t]}$. As expected, N is a Poisson process on T with mean measure Λ if N is a point process where $N_C \sim \text{Poisson}, \Lambda_C, \forall C \in \mathcal{C}$, and whenever $C_1, \dots, C_n \in \mathcal{C}$ are disjoint, N_{C_1}, \dots, N_{C_n} are independent. If Λ is absolutely continuous with respect to Lebesgue measure, its density λ is called the intensity of the Poisson process.

An integrable process $M = \{M_A, A \in \mathcal{A}\}$ is called a *pseudo-strong martingale* if for any $C \in \mathcal{C}$, $E[M_C | \mathcal{G}_C^*] = 0$. The process \bar{X} is a **-compensator* of X if it is increasing and the difference $X - \bar{X}$ is a pseudo-strong martingale. The asymptotic behaviour of a sequence of point processes may be determined by *-compensators as shown in the following theorem specializing Theorem 8.2.2 and Corollary 8.2.3 of Ivanoff and Merzbach (2000) to multivariate point processes on $T = \mathbb{R}^d$ or \mathbb{R}_+^d .

To state this theorem, we consider k point processes $N(1), \dots, N(k)$ all adapted to a common $\mathcal{A}(u)$ -indexed filtration $\{\mathcal{F}_A\}$ and so that with probability one, none of the processes have a jump point in common. The k -variate point process \vec{N} is defined by $\vec{N}_A = \langle N_A(1), \dots, N_A(k) \rangle$ and has (k -variate) *-compensator $\vec{\Lambda} = (\Lambda(1), \dots, \Lambda(k))$ if $\Lambda(i)$ is a *-compensator for $N(i)$ with respect to the common filtration $\{\mathcal{F}_A\}$.

In what follows, “ \rightarrow_P ” denotes convergence in probability and “ \rightarrow_D ” denotes convergence in both finite dimensional distribution and in distribution in the Skorokhod topology if $T = \mathbb{R}_+^d$ (identifying $N_t^{(n)}$ (respectively, N_t) with $N_{A_t}^{(n)}$ (respectively, N_{A_t})). We remark that the Skorokhod topology may be extended to all of the quadrants in \mathbb{R}^d on the space of “outer-continuous functions with inner limits”, and the convergence in the theorem above holds in this case as

well. In the sequel, convergence in the Skorokhod topology will be interpreted in this way.

Theorem 2.1 *Let $(\vec{N}^{(n)})$ be a sequence of k -variate point processes on T adapted to a filtration $\{\mathcal{F}_A\}$ and $(\vec{\Lambda}^{(n)})$ a sequence of corresponding $*$ -compensators. Suppose that for each $A \in \mathcal{A}$ and $i = 1, \dots, k$ the sequences $(N_A^{(n)}(i))$ and $(\Lambda_A^{(n)}(i))$ are uniformly integrable and that $\Lambda_A^{(n)}(i) \rightarrow_P \Lambda_A(i)$ where $\Lambda(i)$ is a deterministic measure on T absolutely continuous with respect to Lebesgue measure. Then $\vec{N}^{(n)} \rightarrow_{\mathcal{D}} \vec{N}$, where $\vec{N} = \langle N(1), \dots, N(k) \rangle$ and $N(1), \dots, N(k)$ are independent Poisson processes with mean measures $\Lambda(1), \dots, \Lambda(k)$, respectively.*

Proof: The proof of this theorem is a straightforward generalization of the techniques used in the proof of Theorem 8.2.2 in Ivanoff and Merzbach (2000) along with an application of Watanabe's characterization of the k -variate Poisson process on \mathbb{R}_+ , see Brémaud (1981, Theorem T6).

We conclude this section by defining empirical point processes on T and stating their $*$ -compensators. Let Y be a T -valued random variable with continuous distribution function F . The *single jump* point process $J = \{J_A = \mathbb{I}_{\{Y \in A\}} : A \in \mathcal{A}\}$ has $*$ -compensator

$$\bar{J}_A = \int_A \mathbb{I}_{\{u \in A_Y\}} (F(E_u))^{-1} dF(u)$$

with respect to its minimal filtration, where $E_t = \{t' \in T : t \preceq t'\}$ (cf. Ivanoff and Merzbach (2000)). Now, suppose that Y_1, \dots, Y_n are i.i.d. with distribution $F(t) = \mathbb{P}(Y_i \leq t)$ and let $\mathcal{F} = \bigvee_{i=1}^n \mathcal{F}^{(i)}$ where $\mathcal{F}^{(i)}$ is the minimal filtration generated by the single jump process associated with Y_i . Then the *empirical point process* $N^{(n)}$ defined by

$$N_A^{(n)} = \sum_{i=1}^n \mathbb{I}_{\{Y_i \in A\}}$$

has $*$ -compensator $\Lambda^{(n)}$ where

$$\Lambda_A^{(n)} = \sum_{i=1}^n \int_A \mathbb{I}_{\{u \in A_{Y_i}\}} (F(E_u))^{-1} dF(u). \quad (1)$$

Example 2.2 If $T = \mathbb{R}_+$ then (1) reads as follows: $A = A_t = [0, t]$ for some $t \geq 0$, \preceq is just \leq , the standard ordering, $E_u = [u, \infty)$. By noting that $F(E_u) = \mathbb{P}(Y_i \geq u) =: \bar{F}(u)$ we have

$$\Lambda_t^{(n)} := \Lambda_{A_t}^{(n)} = \int_{A_t} \sum_{i=1}^n \mathbb{I}_{\{Y_i \in E_u\}} \frac{dF(u)}{\bar{F}(E_u)} = \int_0^t \sum_{i=1}^n \mathbb{I}_{\{Y_i \geq u\}} \frac{dF(u)}{\bar{F}(u)}. \quad (2)$$

Example 2.3 If $T = \mathbb{R}$ then $A_t = [0, t]$ or $A_t = [t, 0]$ depending on the sign of t . We have $s \preceq t$ if $0 \leq s \leq t$, or $t \leq s \leq 0$, where \leq is the standard order on \mathbb{R} . Points with different signs are incomparable. The sets E_u will be either $[u, \infty)$ or $(-\infty, u]$ depending the sign of u . If $u > 0$ then as above $F(E_u) = \overline{F}(u)$, otherwise, if $u < 0$, then $F(E_u) = F(u)$. Now the $*$ -compensator is given by (2) if $t \geq 0$ and if $t < 0$,

$$\Lambda_t^{(n)} := \Lambda_{A_t}^{(n)} = \int_{A_t} \sum_{i=1}^n \mathbb{I}\{Y_i \in E_u\} \frac{dF(u)}{F(E_u)} = \int_t^0 \sum_{i=1}^n \mathbb{I}\{Y_i \leq u\} \frac{dF(u)}{F(u)}. \quad (3)$$

Example 2.4 Let $Y_i = (Y_{i1}, Y_{i2})$, $i = 1, \dots, n$. If $T = \mathbb{R}_+^2$ then (1) reads as follows: $A = A_{\mathbf{t}} = [0, t_1] \times [0, t_2]$ for some $\mathbf{t} = (t_1, t_2)$, $E_{\mathbf{u}} = \{\mathbf{t}' : t'_i \geq u_i, i = 1, 2\}$, $\mathbf{u} = (u_1, u_2)$. By noting that $F(E_{\mathbf{u}}) = \mathbb{P}(Y_{i1} \geq u_1, Y_{i2} \geq u_2) =: \overline{F}(\mathbf{u})$ we have

$$\Lambda_{\mathbf{t}}^{(n)} := \Lambda_{A_{\mathbf{t}}}^{(n)} = \int_{A_{\mathbf{t}}} \sum_{i=1}^n \mathbb{I}\{Y_{i1} \geq u_1, Y_{i2} \geq u_2\} \frac{dF(\mathbf{u})}{\overline{F}(\mathbf{u})}.$$

To extend this example to \mathbb{R}^2 we proceed as in Example 2.3, treating each quadrant separately.

3 Poisson limits at quantiles

3.1 Univariate case

We can use the previous section to determine the limiting behaviour of empirical point processes at quantiles. Consider a sequence $\{Y_n\}$ of i.i.d. real-valued positive random variables with distribution F . Assume now that $F(0) = 0$ and that F is regularly varying at 0 with index $\alpha > 0$, i.e. for all $t \geq 0$,

$$\lim_{x \searrow 0} \frac{F(xt)}{F(x)} = t^\alpha, \quad (4)$$

see e.g. Resnick (1987). This implies that for x in a neighbourhood of 0, $F(x) = \ell(x)x^\alpha$. Here and in the sequel ℓ is a slowly varying function at 0 or at ∞ as required, and it can be different at each appearance.

Let a_n be such that $F(a_n) = n^{-1}$. This ensures that $a_n \sim n^{-1/\alpha} \ell(n)$ for some function ℓ slowly varying at ∞ . Henceforth, we write $c_n \sim d_n$ if $\lim_{n \rightarrow \infty} c_n/d_n = 1$.

Since $a_n \rightarrow 0$ we have

$$nF(a_nt) = \frac{F(a_nt)}{F(a_n)} \rightarrow t^\alpha. \quad (5)$$

Define

$$N^{(n)} = \sum_{i=1}^n \delta_{a_n^{-1} Y_i}.$$

We have by (1)

$$\Lambda_t^{(n)} = \int_0^t \sum_{i=1}^n \mathbb{I}\{a_n^{-1}Y_i \geq u\} \frac{dF(a_n u)}{\overline{F}(a_n u)} . \quad (6)$$

We first reprove the well-known result (see e.g. Resnick (1987, Proposition 3.21) concerning Poisson limits for empirical point processes. An elegant argument can be applied (see e.g. Borisov, 2001, and the references therein) where the law of $N^{(n)}$ is approximated (in the total variation sense and for each n separately) by $Poi(\nu_n)$, the Poisson random measures with $\nu_n(A) = nE(1_{n^{1/k}X_i \in A})$, where the X_i 's are uniform on an appropriately chosen ball. If n is sufficiently large, strong approximation methods yield the coupling of the empirical point processes to a single Poisson random measure, and weak convergence follows. However here we illustrate the martingale approach since the proof easily generalizes to the multivariate context and to establishing simultaneous limits at interior quantiles of F .

Theorem 3.1 *Assume that $F(0) = 0$ and (4) holds. Then the sequence $(N^{(n)})$ converges in distribution to N in the Skorokhod topology on $D[0, \infty)$ where N is a Poisson process with mean measure $\Lambda_t = t^\alpha$ (intensity $\lambda(t) = \alpha t^{\alpha-1}$).*

Proof. Since $N^{(n)}$ is square integrable with bounded second moments (uniformly in n), the conditions of Theorem 2.1 will be satisfied if it is shown that the sequence $(\Lambda_t^{(n)})$ given by (6) converges in L_2 to t^α .

$$\begin{aligned} \mathbb{E}[\Lambda_t^{(n)}] &= \mathbb{E} \left[\int_0^t \sum_{i=1}^n \mathbb{I}\{a_n^{-1}Y_i \geq u\} \frac{dF(a_n u)}{\overline{F}(a_n u)} \right] \\ &= \sum_{i=1}^n \int_0^t \mathbb{P}(a_n^{-1}Y_i \geq u) \frac{dF(a_n u)}{\overline{F}(a_n u)} = \sum_{i=1}^n \int_0^t dF(a_n u) = nF(a_n t) \rightarrow t^\alpha \end{aligned}$$

by applying (5). Using the independence assumption,

$$\begin{aligned} \mathbb{E}[(\Lambda_t^{(n)})^2] &= \int_0^t \int_0^t \sum_{i=1}^n \mathbb{E}[\mathbb{I}\{Y_i \geq a_n u, Y_i \geq a_n v\}] \frac{dF(a_n u)dF(a_n v)}{\overline{F}(a_n u)\overline{F}(a_n v)} \\ &\quad + 2 \int_0^t \int_0^t \sum_{i < j}^n \mathbb{E}[\mathbb{I}\{Y_i \geq a_n u, Y_j \geq a_n v\}] \frac{dF(a_n u)dF(a_n v)}{\overline{F}(a_n u)\overline{F}(a_n v)} \\ &= \int_0^t \int_0^t \sum_{i=1}^n \mathbb{P}(Y_i \geq a_n(u \vee v)) \frac{dF(a_n u)dF(a_n v)}{\overline{F}(a_n u)\overline{F}(a_n v)} \\ &\quad + n(n-1) \int_0^t \int_0^t dF(a_n u)dF(a_n v) \\ &= n \int_0^t \int_0^t \sum_{i=1}^n \mathbb{P}(Y_i \geq a_n(u \vee v)) \frac{dF(a_n u)dF(a_n v)}{\overline{F}(a_n u)\overline{F}(a_n v)} \\ &\quad + n(n-1)(F(a_n t))^2 . \end{aligned}$$

Now, the first term converges to 0, because

$$\begin{aligned} & n \int_0^t \int_0^t \sum_{i=1}^n \mathbb{P}(Y_i \geq a_n(u \vee v)) \frac{dF(a_n u) dF(a_n v)}{\overline{F}(a_n u) \overline{F}(a_n v)} \\ & \leq n \int_0^t \int_0^t \frac{dF(a_n u) dF(a_n v)}{\overline{F}(a_n u)} \leq n [\overline{F}(a_n t)]^{-1} [F(a_n t)]^2, \end{aligned}$$

and $\overline{F}(a_n t) \rightarrow 1$ and $nF^2(a_n t) \rightarrow 0$ as $n \rightarrow \infty$. So, $(\Lambda_t^{(n)})$ converges in L_2 and therefore in probability.

We may extend Theorem 3.1 to the entire line. P_F is the probability measure associated with a distribution F . We say that F is *regularly varying on the right (left)* at u with index α (β) if

$$\lim_{x \searrow 0} \frac{P_F((u, u + xt])}{P_F((u, u + x])} = t^\alpha \quad \left(\lim_{x \searrow 0} \frac{P_F((u + xt, u])}{P_F((u - x, u])} = |t|^\beta \right), \quad (7)$$

for all $t > 0$ and $t < 0$, respectively. Clearly, if F has support $(0, \infty)$ then for $u = 0$ the above condition reduces to (4).

If F fulfills (7), we shall choose a_n and b_n so that

$$F(a_n + u) - F(u) = n^{-1}, \quad F(u) - F(-b_n + u) = n^{-1}. \quad (8)$$

Fix $q \in (0, 1)$ and set $x_q = F^{-1}(q)$ and assume that F fulfills (7) at $u = x_q$. Let

$$N^{(n)}(q) = \sum_{i=1}^n \delta_{a_n^{-1}[Y_i - x_q]} I[Y_i \geq x_q] + \sum_{i=1}^n \delta_{b_n^{-1}[Y_i - x_q]} I[Y_i < x_q]. \quad (9)$$

The argument in the preceding proof can now be repeated for $t > 0$ and $t < 0$ to prove that $\Lambda_t^{(n)}$ converges in L_2 to t^α if $t > 0$ and to $|t|^\beta$ if $t < 0$. Let G be the distribution of $Y_i - x_q$. Thus, $G(s) = F(s + x_q)$. To see that the norming sequences a_n and b_n are chosen appropriately, using the same calculation as in the proof of Theorem 3.1, we have for $t > 0$

$$\begin{aligned} \mathbb{E} [\Lambda_t^{(n)}] &= n \int_0^t dG(a_n u) = n[F(a_n t + x_q) - F(x_q)] \\ &= \frac{F(a_n t + x_q) - F(x_q)}{F(a_n + x_q) - F(x_q)} \rightarrow t^\alpha \end{aligned}$$

by the first part of (7). Moreover, bearing in mind Example 2.3, we have for $t < 0$,

$$\begin{aligned} \mathbb{E} [\Lambda_t^{(n)}] &= n \int_t^0 dG(b_n u) = -n[F(b_n t + x_q) - F(x_q)] \\ &= \frac{F(b_n t + x_q) - F(x_q)}{F(-b_n + x_q) - F(x_q)} \rightarrow |t|^\beta \end{aligned}$$

by the second part of (7). Theorem 2.1 leads to the following Corollary.

Corollary 3.2 Assume (7). Then $N^{(n)}(q) \xrightarrow{\mathcal{D}} N$, where N is a Poisson process on \mathbb{R} with intensity

$$\lambda_t = \begin{cases} \alpha t^{\alpha-1} & \text{if } t > 0 \\ \beta |t|^{\beta-1} & \text{if } t < 0 \end{cases}.$$

The power of the martingale method can be seen when one wants to obtain the asymptotic joint distribution of several $N^{(n)}(q)$.

Theorem 3.3 Let $0 \leq q_1 < q_2 < \dots < q_k \leq 1$ and assume that (7) holds for each $x_{q_i}, i = 1, \dots, k$, with α_i and β_i , respectively. Then

$$\langle N^{(n)}(q_1), N^{(n)}(q_2), \dots, N^{(n)}(q_k) \rangle \xrightarrow{\mathcal{D}} \langle N(1), \dots, N(k) \rangle,$$

where $\langle N(1), \dots, N(k) \rangle$ is a k -variate Poisson process on \mathbb{R} with independent components and marginal intensities $\lambda(i), i = 1, \dots, k$, given by

$$\lambda_t(i) = \begin{cases} \alpha t^{\alpha_i-1} & \text{if } t > 0 \\ \beta |t|^{\beta_i-1} & \text{if } t < 0 \end{cases}.$$

Proof: For clarity, we will consider only the case $k = 2$ and verify the conditions of Theorem 2.1. The general result follows in a straightforward manner.

We begin by observing that it suffices to show joint convergence of

$$\langle N^{(n)}(q_1), N^{(n)}(q_2) \rangle$$

for all $t \in [-K, K]$ for any arbitrary finite constant K . Assume that F is regularly varying on the right and left of x_{q_i} with index α_i and β_i , respectively, $i = 1, 2$. As before, define $a_n^{(i)}$ and $b_n^{(i)}$, $i = 1, 2$ according to (8). Choose M large enough that for $n \geq M$, $[x_{q_1} - Kb_n^{(1)}, x_{q_1} + Ka_n^{(1)}]$ and $[x_{q_2} - Kb_n^{(2)}, x_{q_2} + Ka_n^{(2)}]$ do not intersect. This will ensure that those points Y_j which are jump points of $N^{(n)}(q_1)$ are not jump points of $N^{(n)}(q_2)$ and vice versa.

Consider for $i = 1, 2, 1 \leq j \leq n$ the single jump point process

$$J^{(n,j)}(q_i) = \delta_{(a_n^{(i)})^{-1}[Y_j - x_{q_i}]} I[Y_j \geq x_{q_i}] + \delta_{(b_n^{(i)})^{-1}[Y_j - x_{q_i}]} I[Y_j < x_{q_i}].$$

It is adapted to $\mathcal{F} = \{\mathcal{F}_{A_t} : -K \leq t \leq K\}$, where

$$\mathcal{F}_{A_t} = \begin{cases} \sigma\{\mathbb{I}_{\{Y_j \in [x_{q_i}, x_{q_i} + ta_n^{(i)}]\}}, i = 1, 2; j = 1, \dots, n\} & \text{if } t \geq 0 \\ \sigma\{\mathbb{I}_{\{Y_j \in [x_{q_i} + tb_n^{(i)}, x_{q_i}]\}}, i = 1, 2; j = 1, \dots, n\} & \text{if } t \leq 0. \end{cases}$$

We will compute a *-compensator $\overline{\mathcal{J}}^{(n,j)}(q_i)$ of the single jump process $J^{(n,j)}(q_i)$. We consider only $0 < t < K$ as the argument for $t < 0$ is similar. Let

$$U_t = [x_{q_1} - Kb_n^{(1)}, x_{q_1} + ta_n^{(1)}] \cup [x_{q_2} - Kb_n^{(2)}, x_{q_2} + ta_n^{(2)}].$$

Then for $C = (t, t') \in \mathcal{C}$, it follows that $\mathbb{I}_{\{Y_j \in U_t\}} \in \mathcal{G}_C^*$ and so heuristically, the compensator $\overline{\mathcal{J}}^{(n,j)}(q_i)$ satisfies

$$\overline{\mathcal{J}}_{dt}^{(n,j)}(q_i) = \frac{\mathbb{I}_{\{Y_j \in U_t^c\}} dF(x_{q_i} + a_n^{(i)}t)}{1 - F(U_t)},$$

provided that $[x_{q_1} - Kb_n^{(1)}, x_{q_1} + Ka_n^{(1)}]$ and $[x_{q_2} - Kb_n^{(2)}, x_{q_2} + Ka_n^{(2)}]$ are disjoint intervals. Using arguments similar to those in Ivanoff and Merzbach (2000) it is straightforward to verify that for $n \geq M$ the $*$ -compensator $\Lambda^{(n)}(i)$ of $N^{(n)}(q_i)$ is

$$\Lambda_t^{(n)}(i) = \sum_{j=1}^n \int_0^t \frac{\mathbb{I}_{\{Y_j \in U_s^c\}} dF(x_{q_i} + a_n^{(i)} s)}{1 - F(U_s)}. \quad (10)$$

Exactly as in the comments leading to Corollary 3.2 we have $\mathbb{E}[\Lambda_t^{(n)}(i)] \sim t^{\alpha_i}$ for the appropriate constant α_i , since F is slowly varying on the right at x_{q_i} .

The argument that $\mathbb{E}[(\Lambda_t^{(n)}(i))^2] \rightarrow (t^{\alpha_i})^2$ is also similar to that used in the proof of Theorem 3.1. Also, $N^{(n)}(q_i)$ is square integrable with bounded second moments (uniformly in n). Thus the conditions of Theorem 2.1 have been satisfied and the result follows.

3.2 Multivariate case

Let $\{Y_n\}_{n \geq 1}$ be a sequence of i.i.d. \mathbb{R}^d -valued random variables with continuous distribution F . Following the pattern of the previous section, we may obtain a point process limit if the regular variation index at \mathbf{u} for F depends on the choice of orthant. To be precise, let O_k be the k th orthant and \mathbf{e}_k its associated unit vector, $k = 1, \dots, 2^d$. Then F is regularly varying at \mathbf{u} from orthant $\mathbf{u} + O_k$, with index α_k and rate W_k if for $\mathbf{t} \in O_k$

$$\lim_{x \searrow 0} \frac{P_F((\mathbf{u}, x\mathbf{t} + \mathbf{u}))}{P_F((\mathbf{u}, x\mathbf{e}_k + \mathbf{u}))} = W_k(\mathbf{t}). \quad (11)$$

The function W_k is homogeneous of order α_k , i.e. $W(s\mathbf{t}) = s^{\alpha_k} W(\mathbf{t})$, see e.g. Resnick (1987).

We define $N^{(n)}$ in analogy to (9), i.e.

$$N^{(n)} = \sum_{k=1}^{2^d} \sum_{i=1}^n \delta_{a_{k,n}^{-1}[Y_i - \mathbf{u}]} I[Y_i \in O'_k],$$

where $O'_k = O_k + \mathbf{u}$. More generally, if $\mathbf{u}_j \in \mathbb{R}^d$, $j = 1, \dots, m$, then we may define

$$N^{(n)}(j) := N^{(n)}(\mathbf{u}_j) = \sum_{k=1}^{2^d} \sum_{i=1}^n \delta_{a_{k,n}^{-1}[Y_i - \mathbf{u}_j]} I[Y_i \in O'_{k,j}], \quad (12)$$

where $O'_{k,j} = O_k + \mathbf{u}_j$.

Theorem 3.4 *Assume that the orthant-wise regular variation conditions (11) are satisfied at \mathbf{u}_j , $j = 1, \dots, m$, $\mathbf{x}_j \in \mathbb{R}^d$. For each j , let $N^{(n)}(j)$ denote the \mathbb{R}^d -indexed point process of (12). Then*

$$\langle N^{(n)}(1), N^{(n)}(2), \dots, N^{(n)}(m) \rangle \longrightarrow_{\mathcal{D}} \langle N(1), N(2), \dots, N(m) \rangle$$

where $\langle N(1), N(2), \dots, N(m) \rangle$ is a vector of independent Poisson processes, where the j th component process is parameterized by \mathbb{R}^d and its mean measure is given orthant-wise by the regular variation rates of F at the corresponding \mathbf{u}_j .

Examples of regularly varying distributions are readily constructed. One source of examples are distributions based on copulas as described, for example, in Nelsen (1999) and Section 4.2 below.

4 Applications

Remark 4.1 The values of a_n depend on the exact asymptotic behaviour of the density at x , and certainly will not be known in general. In our applications we consider only the special cases where the slowly varying function $\ell(n)$ is in fact a constant, although unknown. We then apply Theorem 3.1 with the scaling values equal to $n^{-1/\alpha}$. We can define a compensator, $\tilde{\Lambda}^{(n)}$, by (6) where a_n is replaced by $n^{-1/\alpha}$, and the relation to the original definition is given by

$$\tilde{\Lambda}_t^{(n)} = \Lambda_{(n^{-1/\alpha}/a_n)t}^{(n)}.$$

Since $\lim_{n \rightarrow \infty} (n^{-1/\alpha}/a_n) = \omega \in \mathbb{R}$, then

$$\tilde{\Lambda}_t^{(n)} = \Lambda_{(n^{-1/\alpha}/a_n)t}^{(n)} \rightarrow \Lambda_{\omega t}$$

and we have convergence of the empirical point process to a Poisson process with intensity $\omega \alpha t^{\alpha-1}$. For example, if the density of Y at 0 is 8, then the weak limit of $N^{(n)} = \sum_{i=1}^n \delta_{n^{-1/\alpha} Y_i}$ is a Poisson process with intensity $8 \alpha t^{\alpha-1}$. The corresponding changes to the other theorems of the previous section are immediate.

4.1 Local Density Estimation

Consider a sample $\{Y_1, Y_2, \dots, Y_n\}$ with common marginal differentiable distribution F on $[0, 1]$, and assume that its density f is positive on the range $[0, 1]$. Let F_n denote the empirical distribution and define $[t]_n^+ = Y_{(k+1)}$ and $[t]_n^- = Y_{(k)}$ by $Y_{(k)} \leq t < Y_{(k+1)}$. We put $[t]_n^+ = 0$ if $[t]_n^+ < Y_{(1)}$ and $[t]_n^- = 0$ if $[t]_n^- > Y_{(n)}$. A naive nearest-neighbour estimator of the density at t is given by

$$\hat{f}(n, t) = \frac{1}{n} / (([t]_n^+ - t) + (t - [t]_n^-)) . \quad (13)$$

Additional information on nearest-neighbour density estimates can be found in Härdle (1990) or Silverman (1992), including comments on performance, and modifications.

For $t \in (0, 1)$ the fact that F is differentiable and that f is positive (i.e. F is of regular variation index $\alpha = 1$ at t) allows us to write

$$\hat{f}(n, t)/f(t) = 1/f(t) (n([t]_n^+ - t) + n(t - [t]_n^-)) \xrightarrow{\mathcal{D}} 1/f(t)(E_1 + E_2) \quad (14)$$

where E_1 and E_2 are independent exponential variables of mean $1/f(t)$. This convergence follows from Corollary 3.2 and the continuous mapping theorem, and follows the pattern set for extreme value processes as given in Resnick (1987). As each limiting Poisson process has a constant rate function equal to $f(t)$, the distance from t to the first point has an exponential distribution with mean $1/f(t)$. Since such an exponential variable can be written as the product of $1/f(t)$ and an exponential of mean 1, and the sum of two independent mean 1 exponentials is a $\Gamma(2, 1)$ variable, we have identified the limiting distribution of $\hat{f}(n, t)/f(t)$ as Inverse Gamma, $\Gamma^{(-1)}(2, 1)$. The mode, mean and variance of an Inverse Gamma density of parameters (α, β) are $\beta/(\alpha + 1)$, $\beta/(\alpha - 1)$ (for $\alpha > 1$) and $\beta^2/((\alpha - 1)(\alpha - 2))$ (for $\alpha > 2$), respectively. Thus we see that this naive estimator of $f(t)$ has mode $f(t)/3$, mean $f(t)$ and infinite variance.

This development can be easily extended to estimators based on the k lower nearest neighbours and k upper nearest neighbours. As above, asymptotically the spacings between consecutive neighbours are independent exponential variables with mean $1/f(t)$. The asymptotic joint density is the product of $2k$ exponentials, and the sufficient statistic is just the total distance from the lower k th-nearest neighbour of t , $[t]_n^{-k}$, to the upper k th-nearest neighbour, $[t]_n^{+k}$.

Corollary 4.2 *The asymptotically uniformly minimum variance unbiased estimator ($k > 1$) is*

$$\hat{f}_k(n, t) = \frac{(2k - 1)/n}{[t]_n^{+k} - [t]_n^{-k}},$$

and $\hat{f}_k(n, t)/f(t)$ has an asymptotic $\Gamma^{(-1)}(2k, 1)$ density.

Using this result we can consequently compute approximate confidence intervals for $f(t)$ or construct tests. If k is fixed, Theorem 3.3 also identifies the limiting distribution of

$$\langle \hat{f}_k(n, t_1), \hat{f}_k(n, t_2), \dots, \hat{f}_k(n, t_m) \rangle$$

as given by a vector of m independent scaled inverse Gamma variables. Consequently we can obtain the limiting distribution of expressions such as approximate integrals,

$$\hat{E}(g(Y)) = \sum_{i=1}^m g(t_i)(\hat{f}_n(t_i)),$$

even for arbitrary dimension (Theorem 3.4) with appropriate norming.

Remark 4.3 On the other hand, we see that $\hat{f}_k(n, t)/f(t)$ still has an Inverse Gamma distribution, but with finite variance for $k \geq 1$. It has asymptotic variance $1 + 1/(2k - 2)$, and so remains inherently random regardless of the fixed number of nearest neighbours used in the estimate. Nearest-neighbour methods have become popular in data mining, classification and computing applications, and rapid algorithms exist for finding the k nearest neighbours to a point t even in high dimensions. The above discussion shows that even in highly regular cases, the best k -nearest-neighbour density estimate will not converge in probability to the desired limit, and remains random.

As an example of a test that can be constructed using the results of this paper, we consider the null hypothesis that F is regularly varying as ωt from the right at 0 for some $\omega > 0$ (e.g. $F'(0) = \omega > 0$). We take the alternative to be where F varies as ζt^2 from the right for some $\zeta > 0$ (i.e. $F'(0) = 0$). The maximum likelihood under the null hypothesis is proportional to $([t]_n^{+k})^{-k}$, and that under the alternative proportional to $([t]_n^{+k})^{-k} \times \prod_{i=1}^k ([t]_n^{+i} / [t]_n^{+k})$.

Corollary 4.4 *The likelihood ratio test based on the $k \geq 2$ upper nearest neighbours rejects when*

$$\prod_{i=1}^{(k-1)} ([t]_n^{+i} / [t]_n^{+k})$$

is too large. Under the null hypothesis, the distribution of this product is given by the product of $k - 1$ independent uniform variables on $[0, 1]$.

When $k = 2$ we obtain an intuitively reasonable test that rejects when the distance from 0 to $[t]_n^{+1}$ is much larger than that from $[t]_n^{+1}$ to $[t]_n^{+2}$, and so indicates the presence of a “gap” in the distribution.

4.2 Multivariate extremes

Let $\{(Y_{n1}, Y_{n2})\}_{n \geq 1}$ be an i.i.d. sequence of bivariate random vectors. To focus on the bivariate dependence structure rather than the marginal distributions, we assume that (Y_{11}, Y_{12}) has a copula C and standard uniform marginals, see Nelsen (1999). We want to characterize

$$\mathbb{P}(Y_{11} > 1 - xt_1, Y_{12} > 1 - xt_2)$$

as $x \searrow 0$. If Y_{11} and Y_{12} are independent, then the above probability factors and we can apply standard extreme value methods (e.g. Resnick, 1987) to the marginals. However, if Y_{11} and Y_{12} are dependent but the maxima are asymptotically independent then the extreme value methods fail; see Fougères (2004) for a general discussion of this problem. For most known families of copulas which have the asymptotic independence property, we have (cf. Hefferman, 2000)

$$\mathbb{P}(Y_{11} > 1 - xt_1, Y_{12} > 1 - xt_2) \sim cx^2. \quad (15)$$

By the results of this paper the appropriate scaling to obtain a point process limit for the joint extremes is $a_n = n^{-1/2}$, and not the $a_n = n^{-1}$ that would be used to normalize the marginal variables individually. Note, moreover, that the methods of this paper are “dimension free”, and so we can address multivariate copulas of any dimension.

Further we can address the joint extreme value behaviour of copulas with the asymptotic independence property but where (15) is not satisfied. Consider the case when C is the bivariate normal copula with correlation $\rho \in (0, 1]$ – i.e. $C(x, y)$ is given by a joint normal distribution function at $(\Phi^{-1}(x), \Phi^{-1}(y))$ with standard marginals and correlation ρ . We have

$$\mathbb{P}(Y_{11} > 1 - xt_1, Y_{12} > 1 - xt_2) \sim x^{2/(1+\rho)} g(t_1, t_2)$$

for a function g as $x \searrow 0$, and so

$$\lim_{x \searrow 0} \frac{\mathbb{P}(Y_{11} > 1 - xt_1, Y_{12} > 1 - xt_2)}{\mathbb{P}(Y_{11} > 1 - x, Y_{12} > 1 - x)} = \frac{g(t_1, t_2)}{g(1, 1)},$$

for $t_1, t_2 \geq 0$. For $\mathbf{u} = (1, 1)$ and $t_1, t_2 \leq 0$, formula (11) is satisfied with

$$W(t_1, t_2) = \frac{g(-t_1, -t_2)}{g(1, 1)}.$$

Applying the results of Section 3.2, we can characterize the asymptotics of joint extremes for a normal copula.

Corollary 4.5 *Assume that $\{\mathbf{Y}_n = (Y_{n1}, Y_{n2})\}_{n \geq 1}$ are independent, have a common normal copula of parameter ρ and uniform marginals. Then for $\mathbf{u} = (1, 1)$ and $a_n = n^{-(1+\rho)/2}$,*

$$N^{(n)} = \sum_{i=1}^n \delta_{a_n^{-1}[\mathbf{Y}_i - \mathbf{u}]}$$

converges to a Poisson process on \mathbb{R}_-^2 with mean measure $W(\cdot, \cdot)$.

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